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CROP IDENTIFICATION AND GROWTH MONITORING ALONG THE SEASON WITH RADARSAT-2 QUAD-POLARIZED TIME SERIES IN BELGIUM

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ABSTRACT

With changes in the climate system, obtaining information on crop growth in order to derive early estimates of yields is necessary. Remote sensing allows collecting frequent crop development indications such as the Leaf Area Index (LAI). Although the interaction between linear polarized microwaves and agricultural targets has been studied widely, the implementation of a method that takes benefits of all linear polarizations to optimize the LAI estimation is necessary. Simultaneous to the acquisition of 11 RADARSAT-2 in 2013, LAI over winter wheat fields was measured. The Water Cloud Model (WCM) was implemented to derive LAI values from each polarization. A combination of the retrieved LAI and their associated errors for each polarization was then computed to improve LAI estimation. To investigate the potentiality of applying the model to the agricultural region, a crop classification model to identify winter wheat field was developed using multi-year parcel's crop sequence. This model automatically extracts a training sample. The classification yielded an accuracy of 89%.

***Index Terms*—** LAI, Winter Wheat, Radarsat-2, crop mask, multi-polarization. Water Cloud Model.

1. INTRODUCTION

With world trade globalization and changes in the climate system, obtaining information on crop status in order to derive early estimates of yields is of common purpose. Remote sensing allows collecting frequent crop development indications such as the Leaf Area Index (LAI). LAI is a biophysical variable of major importance for crop monitoring as well as for coupling Earth Observation with crop growth models in the perspective of yield forecasting.

In order to get accurate estimation of LAI, the retrieval should be crop specific [1]. Therefore, the initial step of the processing is to define crop specific masks by classifying the images. Generally, it is difficult to have an accurate crop mask at the beginning of the season [2]. Indeed most of the classification algorithms rely on a training data set with the information on the crop type of several agricultural parcels collected in the field. At the beginning of the season, most of the crops are not yet planted or are at a too early stage to be properly identified. This often delays the map availability to the end of the season which reduces its value and usability. Considering crop rotation and parcels' cultivation sequence could improve both the timeliness of the map and its accuracy.

The RADARSAT-2 sensor presents a quad-polarization mode that multiplies information in one image by the simultaneous acquisition of four linear polarizations. Furthermore, SAR signal is very sensitive to plant water content, a variable highly correlated with the LAI during the growing phase [3]. The interaction between linear polarized microwaves and agricultural targets has been studied widely [4], far less is undertaken in the definition of a method that takes benefits of all linear polarizations to optimize the LAI estimation. During 2013, a serie of RADARSAT-2 images, quad-polarizations and at different incidence angles, were acquired in Belgium. Over the SAR data acquisition time series, we repetitively gathered ground data (LAI, volumetric soil moisture and phenological stages and crop types) for a large set of fields.

The overarching objective is to improve wheat LAI estimation and to reduce its associated uncertainty thanks to the potential of polarized C-band SAR sensors while using the semi-empirical Water Cloud Model [3]. The second objective is to investigate the use of crop type transition matrices to: i) predict the crop type at the beginning of the growing season without remote sensing data; ii) extract automatically a reliable training sample and improve the predicted class by means of a classification.

2. STUDY SITE AND DATA

During 2013, 11 RADARSAT-2 Fine Quad Pol images have been acquired (Tab. 1) over winter wheat fields in the agricultural Loamy region in central Belgium. Their incidence angle is heterogeneous and varies from 22° to 44°. The SAR preprocessing chain includes multi-looking, geocoding and radiometric calibration to convert SLC products into Geocoded Terrain Corrected (GTC) products with a spatial resolution of 12.5 m. The per-field mean backscattering coefficient and local incidence angle were extracted for each parcel. A buffer zone of 25 m was used to discard mixed pixels along field borders. In this study, we use three different subsamples to test the WCM. The first subsample contains four SAR acquisitions occurred during the first part of the growing season (until heading), from 7th May to 14th June. In fact, during this early growing stage, the wheat crop presents an attenuation of the backscattering signal with the increase of fresh biomass [5]. The second subsample takes into account seven acquisitions from 24th April to 18th July. The last subsample is the same with only incidence angle upper 38°.

Table 1: Eleven RADARSAT-2 images were acquired over the Belgian loamy agricultural region in 2013.

Date	Pass direction	Inc. angle (°)	*Vm* (%)	LAI (m²/m²)	N. obs
2013-Mar-07	ASC.	20.9-22.9	20,60	0,35	13
2013-Mar-27	ASC.	39.2-40.7	18,97	0,40	13
2013-Apr-10	ASC.	30.2-32	23,17	0,45	13
2013-Apr-24	ASC.	20.9-22.9	15,43	0,78	13
2013-May-07	ASC.	42.8-44.1	13,47	1,28	13
2013-May-14	ASC.	39.2-40.7	19,13	1,64	13
2013-May-31	ASC.	42.8-44.1	23,70	2,77	13
2013-Jun-14	ASC.	35.4-37	16,23	4,46	13
2013-Jun-24	ASC.	42.8-44.1	19,97	4,78	13
2013-Jul-18	ASC.	42.8-44.1	10,47	3,85	13
2013-Aug-11	ASC.	42.8-44.1	14,83	2,58	13

The Integrated Administration and Control System (IACS), a vectorial and annually updated GIS which contains information on most of the agricultural parcels in the Walloon region of Belgium (field limits and crop type) is used to compute the transition matrices. Only fields from the loamy agricultural region are kept in order to improve the spatial consistency. For the classification, the selection is enforced to the region covered by the RADARSAT-2 images.

The winter wheat fields selected in Belgium are rectangular-shaped with a size equaling 4 to 10 hectares. In situ LAI measurements were collected on the ground during intensive field campaigns at the beginning of the winter wheat growing seasons. The LAI was measured by taking hemispherical photographs processed with the CAN-EYE software. In each field, the LAI was calculated from minimum 10 distributed measurements per field. These measurements were taken at a minimum distance of 30 meters away from the field limits to avoid any border effects. Surface volumetric soil moisture was estimate by the Soil, Water, Atmosphere and Plant model (SWAP) [6].

3. METHODOLOGY

3.1 Transition matrix generation and classification

The first step consisted in finding the optimal time window for the transition matrix. One, two, three, four and five years (2007-2012) crop sequences were tested to predict the 2013 crop mask. The predicted class with the maximum probability related to each crop sequence was assigned at each parcel of 2013. After assessing the accuracy of the prediction without classification, the transition matrix of the crop sequence with the most accurate result was kept for predicting the crop type in 2013. At this stage, crop cover was reduced to three classes for the first crop type prediction: winter wheat, grassland and other crops. Second, a training dataset was extracted for the classification by removed the parcels with a maximum transition probability below 50 %. The trimming step remove unreliable predictions from the data set that could reduce the classifier's accuracy. This training set is used to train a Random Forest classifier.

3.2 LAI

Next to various empirical relationships developed to retrieve crop variables from SAR data, the Water Cloud Model have been widely used for agricultural applications. In this model, the backscattering coefficient (σ^0_{total}) can be formulated as the incoherent sum of the direct contribution of the vegetation (σ^0_{veg}) and the contribution of the soil (σ^0_{soil}) attenuated by the vegetation (t^2):

$$\sigma^0_{total}\left[m^2/m^2\right] = \sigma^0_{veg} + t^2\sigma^0_{soil} \qquad (1)$$

with: $$\sigma^o_{veg}\left[m^2/m^2\right] = A\cos\theta(1-t^2) \qquad (2)$$

$$t^2 = \exp(-2B.LAI/\cos\theta) \qquad (3)$$

$$\sigma^o_{soil}(dB) = C.V_m - D \qquad (4)$$

where θ is the local incidence angle, V_m is the volumetric soil moisture, *A*, *B*, *C*, *D* the model coefficients. Parameter *A* is related to the scattering albedo of the canopy and *B* to its vertical depth [7]. *C* is assumed to be constant and represents the sensitivity of the signal to the soil moisture, *D* is assumed to be specific of the radar configuration and the soil roughness [7].

Calibration of the WCM was run for each polarization with the four variables needed: LAI, surface soil moisture (V_m), SAR backscattering coefficient (σ^0_{total}) and local incidence angle (θ). The four parameters (*A*, *B*, *C* and *D*) are calibrated by non-linear regression. Non-linear regression relies on the minimization of the Sum of Squared Deviations (SSD) between the measured signal and the corresponding simulated values. The inverse equation (5) was used to estimate winter wheat LAI from the backscattering coefficient, the local incidence angle and the surface soil moisture.

$$LAI_{sim} = \ln[\frac{10^{(\sigma_{dB}{}^0/10)} - A\cos\theta}{10^{((C*Vm-D)/10)} - A\cos\theta}].\frac{\cos\theta}{-2*B} \qquad (5)$$

4. RESULTS AND DISCUSSION

4.1. Crop mask

The prediction errors for the area of interest ranged from 46% with a two year sequence to 40% with a six years sequence (Tab. 2). The largest improvement occurs when considering at least three years. Consequently, the transition matrix with six years was kept to predict the crop types in 2013.

Table 2. Prediction error for 2013 of transition matrices with different crop sequence lengths (2007-2012) for the agricultural loamy region.

Year of the crop sequence	Error
07-08	0.463
08-09	0.463
09-10	0.463
10-11	0.463
11-12	0.463
07-08-09	0.429
08-09-10	0.413
09-10-11	0.412
10-11-12	0.412
07-08-09-10	0.403
08-09-10-11	0.404
09-10-11-12	0.401
07-08-09-10-11	0.402
08-09-10-11-12	0.397
07-08-09-10-11-12	0.396

After the prediction, the crop types were aggregated to the three classes of interest. The class prediction according to the transition model reaches an overall accuracy of 83% (Tab. 3). The winter wheat class is predicted with the worst combination of producer and user accuracy (77% and 78%, respectively).

Table 3. Confusion matrix of the prediction for 2013 using the 6 years transition matrix (2007-2012) for the region covered by RADARSAT-2.

	Other Crops	Winter Wheat	Grassland	Total	Users
Other Crops	4096	632	366	5094	0.8041
Winter Wheat	406	2137	193	2736	0.7811
Grassland	10	3	1499	1512	0.9914
Total	4512	2772	2058	9342	
Producers	0.9078	0.7709	0.7284		0.8277

After the trimming, only the parcels with more than 50% of probability were kept as training sample. This sample had an overall accuracy of 89%, an increase of over 6 percent compared to the initial prediction. The Winter Wheat class is the one benefiting the most of the trimming: the producer and user accuracies became 82% and 92%, respectively. A random forest classifier was trained on the mean backscattering coefficients by field. The entire data set was classified with 89% of overall accuracy (Tab. 4). The major improvements were the reduction of the commission error for the Winter Wheat class (22% to 9%) and the omission error for the Grassland class (22% to 7%).

Table 4. Confusion matrix of the prediction for 2013 using a Random Forest classifier trained with a sample defined by the transition matrix.

	Other Crops	Winter Wheat	Grassland	Total	Users
Other Crops	3972	646	118	4736	0.8387
Winter Wheat	202	2324	1	2527	0.9197
Grassland	11	2	1490	1503	0.9914
Total	4185	2972	1609	8766	
Producers	0.9491	0.782	0.926		0.8882

4.2. Water Cloud Model

First, the Water Cloud Model was calibrated for different polarization and subsample. The mean Sum of Squared Deviations (SSD) between the measured signal and the corresponding simulated values varies from 0.56 to 1.55 dB. Fig.1 shows the calibration results for the dataset comprising 4 RADARSAT-2 acquisitions during the vegetative phase with an incidence angle upper 35°. The VV and HV polarization calibration seem the most interesting because of its much larger range of observed backscattering coefficient.

Concerning the values of calibrated parameters A, B, C and D and their variances for the different configuration of the dataset, every data set show a higher variation of the parameters related to the soil moisture (C and D) especially the third configuration (data not shown).

Winter Wheat LAI estimates were obtained after model inversion from the backscattering coefficient, the local incidence angle and the surface soil moisture. RMSEs on LAI estimation vary from 0.53 to 1.64 m²/m² (Tab. 5). The error affecting the LAI estimation was calculated thanks to a comparison with the reference LAI values from the calibration data set. Fig.2 presents the simulated LAI as a function of reference LAI for each polarization for the vegetative phase of the dataset. The results obtained during the vegetative phase are better than to the others configurations. The VV and HV polarizations show the most promising results with a smaller RMSE compared to the HH polarization.

Table 5. LAI retrieval results after calibration and validation of the water cloud model.

Data set	**Polarization**	**RMSE on LAI**	**Std on LAI**
Vegetative phase - 4 acquisitions	VV	0.67	0.11
	HH	1.24	0.74
	HV	0.55	0.13
	Pond	0.53	0.05
Whole growing season - 7 acquisitions	VV	0.98	0.32
	HH	1.20	0.40
	HV	1.44	0.24
	Pond	0.87	0.09
Whole growing season - θ>38° - 5 acquisitions	VV	1.64	0.16
	HH	0.85	0.60
	HV	0.69	0.37
	Pond	1.09	0.09

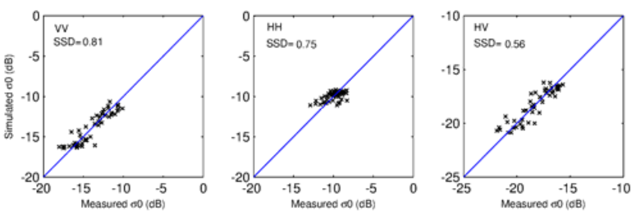

Fig.1 Measured versus simulated backscattering coefficient after Water Cloud Model calibration for VV, HH and HV polarizations during the vegetative phase of winter wheat (n=49).

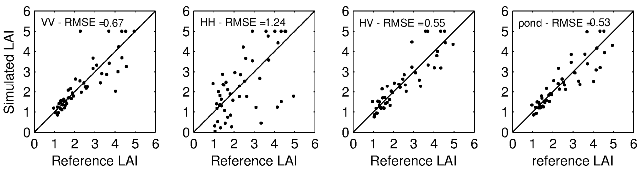

Fig.2 Reference LAI versus simulated LAI, after WCM inversion using VV, HH and HV polarizations and, after LAI recalculation by weighting the three polarizations during the vegetative phase of winter wheat (n=49).

5. CONCLUSIONS

The HV and VV polarizations were found the most relevant polarizations to retrieve wheat LAI through the Water Cloud Model. A combination of the retrieved LAI and their associated errors for each polarization was computed to improve the LAI estimation. Results indicate that this LAI estimation is often enhanced and its uncertainty reduced by comparison with the ones retrieved from a single polarization. Using a restricted dataset limited to the vegetative phase enhance the LAI retrieval, this opportunity should be tested on other dataset. The wheat crop mask – necessary to retrieve LAI on a larger scale – is extractable at the beginning of the season using the parcel's crop sequence. Its accuracy can be improved by selecting the most reliable prediction to class SAR time-series.

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